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Big Data Driven Cognitive Computing System for Optimization of Social Media Analytics

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ABSTRACT Big data-driven cognitive computing can be employed to resolve the failures faced during big data analytics. In E-projects portfolio problem, big data-driven decision-making has a great importance in web developing environments. E-projects portfolio problem deals with choosing a set of the best investment projects on social media such that maximum return with minimum risk is achieved. This paper develops a hybrid fuzzy multi-objective optimization algorithm, namely, NSGA-III-MOIWO which is based on non-dominated sorting genetic algorithm III (NSGA-III) and multi-objective invasive weed optimization (MOIWO) in order to optimize E-projects portfolio problem on social media. Here, the objectives are to simultaneously minimize variance, skewness and kurtosis as the risk measures and maximize the total expected return. To evaluate the performance of the proposed hybrid algorithm, the data derived from 125 active E-projects in a web development company in Iran over the period 2017-2018 are used. Experimental results indicate that NSGAIII-MOIWO outperforms NSGA-III and MOIWO in finding efficient investment boundaries in E-project portfolio problems. Finally, an efficient comparative analysis is performed to test the performance of NSGA-III-MOIWO against some well-known multi-objective algorithm.

INDEX TERMS Big data-driven cognitive computing system, Social media, E-projects portfolio problem, Fuzzy system

I. INTRODUCTION

Nowadays web development projects have attracted a lot of attention from investors in different countries. In this field, E-portfolio is a new concept that tries to find the best portfolio for social media investors. E-portfolio is introduced first by Chantanarungpak [1] and is the use of computer technology to collect and store portfolio in various formats. It is fulfilled by connecting each work which eases the access and is modified to show what the e-portfolio developers have learned. E-projects portfolio is a new and applicable optimization problem which tries to find the best social media-based projects with the highest return and lowest investment risk and is inspired by the modern portfolio problem presented by Markowitz [2]. One of the major problems in developing countries, including Iran, is the lack of a suitable investment platform for individuals and organizations. One of the key factors for web developing companies is the active participation of people in E-projects. The most important issue regarding investing in an E-project-based company is the selection of the most appropriate investment bonds and the formation of E-projects portfolio that is optimal. On the other hand, big data analysis by humans is a time-consuming task and therefore the use of efficient cognitive systems can be employed to process this large amount of data [3-4, 35]. In E-project portfolio problem, big data-driven decision-making has a great importance in web developing environments. As an effective tool, the cognitive computing-based system works by intercepting the command and then drawing inferences and proposing possible solutions. Furthermore, big data provided from social media can be managed effectively using big data analytics process. Accordingly, customer behavior can be recognized and five characteristics of big data, which are known as volume, value, velocity, variety and veracity, can be handled. These features provide the required input information for E-projects portfolio optimization. The aforementioned discussion reveals that there is a necessity of a general and multi-purpose approach to optimize the E-projects portfolio selection (EPPS) problem. Hence, the objectives and contributions of this paper are stated as follows:

- Firstly, a mathematical model is proposed to address the E-projects portfolio based on social media and big data-driven computing. The mathematical model includes minimizing risk in terms of variance, skewness and kurtosis measures, as well as maximizing expected returns.
- Secondly, a hybrid algorithm, namely, NSGA-III-MOIWO is proposed. It takes the advantages of non-dominated sorting genetic algorithm III (NSGA-III) and multi-objective invasive weed optimization (MOIWO) algorithms at the same time to deal with the complexity of the problems.
- Thirdly, the fuzzy system is incorporated with NSGA-III-MOIWO to handle the situation of uncertainty during EPPS.
- Fourth, extensive computer simulations are conducted to evaluate the performance of the proposed algorithm.

To verify the performance of the proposed algorithm, it was implemented in a range of problems in a construction company in Iran. The data derived from 125 active projects in a web developing company in Iran over the period 2017-2018 are used for experimentation. NSGA-IIIMOIWO outperforms NSGA-III and MOIWO in finding efficient investment boundaries in E-projects portfolio problems. In addition, the proposed NSGA-III-MOIWO is compared against other well-known multi-objective algorithms using the analysis of variance (ANOVA) statistical test.

The organization of the remaining sections is as follows. Section II includes a review of the related works. In Section III, the proposed problem of the study is discussed and formulated. Our proposed hybrid algorithm is presented in Section IV and the numerical experiments are provided in Section V. Moreover, Section VI represents a discussion of the results and, finally, the concluding remarks and future research directions are given in Section VII.

II. RELATED WORK

This section highlights the challenges and existing solutions for the industrial EPPS problem. Kolm et al. [5] extensively reviewed the 60-year history of portfolio optimization and examined various models presented in this area. In the study, they investigated various types of models presented in the field of optimization of stock portfolios under certain, uncertain and different risk types conditions. Literature reveals that the industrial portfolio selection problems are complex in nature, hence it grabbed the attention of the researchers who are involved in metaheuristics algorithmic research. From this perspective, Ehrgott et al. [6] presented a multi-objective model which was influenced by the original Markowitz model [2]. Five functions were used to represent risk and expected return and considered as objective functions for the metaheuristic algorithms. The proposed a multi-objective model and utilized three popular meta-heuristic algorithms, namely, genetic algorithm (GA) [32], simulated annealing (SA) [33] and tabu search (TS) [34] for solving the five functions. Oh et al. [7] implemented a GA for the stock portfolio optimization problem by considering the index fund management. The index fund is one of the most common strategies in portfolio management. They could demonstrate that GA has a significant advantage over the conventional portfolio mechanism and provide an average performance for the flat market. Macedo et al. [8] implemented two very popular multi-objective EAs, namely, NSGA-II [9] and Strength Pareto Evolutionary Algorithm 2 (SPEA 2) [10]. They also used and compared the technical analysis indicators to have better outcomes in relation to risk return exchanges. Recently, Babazadeh and Esfahanipour [11] presented a novel multi-period portfolio optimization model based on mean Value-At-Risk (VaR) with consideration of operational and transaction constraints. To solve the proposed problem, they developed an enhanced NSGA-II algorithm and investigated its performance against three other multiobjective algorithms using benchmark problems. Recognizing sources of uncertainty in the real world, recently, attentions have been paid to the portfolio optimization problem under uncertainty. Deng et al. [12] applied a new maximin model to select portfolios with the uncertainty for both randomness and estimation in inputs. Then, Huang's research works [13-14] on portfolio optimization using fuzzy logic can be considered important studies conducted recently. Tavana et al. [15] developed a comprehensive methodology consisting of Data Envelopment Analysis (DEA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and integer programming to solve a fuzzy portfolio selection problem. Among other studies which employed fuzzy logic in their research, Perez et al. [16], considered applying fuzzy constraints, Saborido et al. [17] and Liagkouras et al. [18], developed multiobjective optimization algorithms, Liu et al. [19] employed the methods of Multiple-Criteria Decision-Making (MCDM) and Liu [20], introduced a new fuzzy modeling. Similarly, some studies used uncertain approaches including stochastic programming [21] and robust optimization [22].

After reviewing and scrutinizing related research works, the identified research gap is the lack of an efficient metaheuristic algorithm to optimize risk and expected return simultaneously in E-projects portfolios. On the other hand, the optimizing risk by using a single measure cannot encompass all possible risks in the E-projects. To the best of our knowledge, the risk criteria including kurtosis, skewness and variance were not studied at the same time in the literature. These concurrent considerations make the study close to the real-world condition. Therefore, the focus of this study is on the application of a hybrid NSGA-III-MOIWO algorithm developed based on the NSGA-III and MOIWO, as one of the most recent and most efficient multi-objective evolutionary algorithms to solve the E-projects portfolio optimization problem considering expected return as well as risk criteria including variance, skewness and kurtosis simultaneously.

III. Problem Statement

As stated in the previous section, for the first time, in 1952, Markowitz proposed a model for asset portfolio selection using the mean and variance. He formulated the problem as a quadratic programming model with the goal of minimizing the variance of assets sets, provided that the expected return is equal to a constant value. The classic Markowitz's model had several drawbacks which was first discussed by Seyedhosseini et al. [23].

Here, we develop a modified fuzzy model based on the Markowitz's model, in which the risk aversion coefficient is used, can be presented by (1)-(6) as follows [24]:

$$\text{minimize } \lambda\left[\sum_{i=1}^{n}\sum_{j=1}^{n} z_i x_i z_j x_j \sigma_{ij}\right] - (1-\lambda)\left[\sum_{i=1}^{n} z_i x_i \mu_i\right] \tag{1}$$

subject to

$$\sum_{i=1}^{n} x_i = 1, \tag{2}$$

$$\sum_{i=1}^{n} z_i = K, \tag{3}$$

$$\varepsilon_i z_i \le x_i \le \delta_i z_i \quad (i = 1, \dots, n), \tag{4}$$

$$z_i \in [0,1] \quad (i = 1, \dots, n), \tag{5}$$

$$x_i \ge 0 \quad (i = 1, \dots, n). \tag{6}$$

where x_i and x_j are the proportions of total capital budget invested in E-projects i and j, respectively. Moreover, σ_{ij} is the risk of selecting E-projects i and j simultaneously, and μ_i represents the expected return value for i^{th} project. Moreover, K is the portfolio size and the number of selected E-projects, and λ is a parameter that takes value between 0 and 1. For instance, assume $\lambda = 0$, then the total amount of the weighting coefficient is assigned to the return, ignoring the risk, so the portfolio with the highest return is chosen whereas by assuming $\lambda = 1$, the total weighting factor is assigned to the risk factor, regardless of the return, so the portfolio with the minimum risk is selected.

Equation (1) represents the objective function for the minimization of risk. When λ takes value between zero and one, portfolios are optimized by considering both risk and return factors. When the value of the coefficient λ increases, the objective of risk minimization becomes more important. As a result, the value of coefficient $(1-\lambda)$ is decreased, then the objective of return maximization becomes less important. Equation (2) shows that the sum of investments for all stocks equals the total amount of budget and forms the relationship between all decision variables. Equation (3) indicates the maximum number of E-projects to be selected where z_i is a binary variable which can take value 1 when i^{th} project is in the E-project portfolio. Equation (4) shows that ε_i and δ_i are the lower and upper bound of the i^{th} variable (i^{th} project in the portfolio).

A. Fuzzy Portfolio Optimization Model

In classical decision-making, the optimal decision is made between possible decisions in the face of problem constraints and with the objectives of the optimization model. The parameters of objective functions and constraints are assumed to be deterministic in classic decision making, while in fuzzy decision making it is possible to define the uncertain and approximate parameters of the objective function and constraints. So it seems that using a fuzzy decision can be very useful when we face the lack of knowledge, experience or information that can be definitively defined.

In order to formulate the portfolio mathematical model with an uncertain return, each uncertain parameter is considered as a triangular fuzzy number. The distribution of the triangular fuzzy number is represented in Fig. 1. Moreover, the membership function of a triangular fuzzy number is presented in (7).

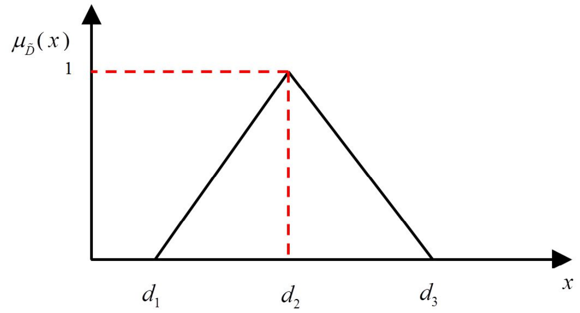

FIGURE 1. Triangular fuzzy number.

$$\mu_{\tilde{D}}(x) = \begin{cases} \dfrac{(x-d_1)}{(d_2-d_1)}, & d_1 \le x < d_2, \\ \dfrac{(d_3-x)}{(d_3-d_2)}, & d_2 \le x < d_3, \\ 0, & \text{Otherwise.} \end{cases} \tag{7}$$

Now, consider ξ_i as the fuzzy number for the return of each project, and x_i as an investment ratio required for project i. Essentially, the return (ξ_i) for each project is calculated using (8), where p_i, p_i' and d_i are the value of project i at the present time, the estimated price during the intended period and the derivation of estimated price, respectively.

$$\xi_i = \frac{p_i' + d_i - p_i}{p_i} \quad (i = 1, \dots, n). \tag{8}$$

Since p_i' and d_i are uncertain variables in the present time, they are regarded as fuzzy variables, where ξ_i is a fuzzy triangular parameter as $(p_i' - d_i, p_i', p_i' + d_i)$. By the consideration of this assumption, the return of a project portfolio with n project with a weight vector $x_1, x_2, x_3, \dots, x_n$ meaning $\xi = \sum_{i=1}^{n} x_i \xi_i$ is also a fuzzy variable.

In order to formulate the mean and deviation indicators of the portfolio, the credibility of a fuzzy number (Cr) is applied as the mean of its possibility and necessity. A fuzzy parameter might fail even if its occurrence possibility is equal to one and it might occur even if its necessity is equal to zero. That is why the credibility criterion uses the combination of these two functions and in fact, plays the role of occurrence possibility in fuzzy conditions. According to Liu and Liu [24], the mean variance, skewness and kurtosis of a fuzzy parameter is calculated based on (9)-(12), respectively:

$$E[\xi_i] = \int_0^{\infty} Cr\{\xi_i \geq r\}dr - \int_{-\infty}^{0} Cr\{\xi_i \leq r\}dr, \tag{9}$$

$$Var[\xi_i] = \int_0^{\infty} Cr\{(\xi_i - E[\xi_i])^2 \geq r\}dr, \tag{10}$$

$$Sk[\xi_i] = \int_0^{\infty} Cr\{(\xi_i - E[\xi_i])^3 \geq r\}dr, \tag{11}$$

$$Ku[\xi_i] = \int_0^{\infty} Cr\{(\xi_i - E[\xi_i])^4 \geq r\}dr. \tag{12}$$

where *r* is a random variable in the range of lower bound and upper bound of the predefined fuzzy number. Now, instead of the criterion of variance, we can use Skewness (*Sk*) and Kurtosis (*Ku*). To provide efficient solutions that fully cover the risk of the E-project portfolio selection problem, a quad-objective model is represented through (13)-(16):

minimize

$$Var = \left[\sum_{i=1}^{n} x_i [\int_0^{\infty} Cr\{(\xi_i - E[\xi_i])^2 \geq r\}dr]\right] \tag{13}$$

minimize

$$Sk = \left[\sum_{i=1}^{n} x_i [\int_0^{\infty} Cr\{(\xi_i - E[\xi_i])^3 \geq r\}dr]\right] \tag{14}$$

minimize

$$Ku = \left[\sum_{i=1}^{n} x_i [\int_0^{\infty} Cr\{(\xi_i - E[\xi_i])^4 \geq r\}dr]\right] \tag{15}$$

minimize

$$R = \left[\sum_{i=1}^{n} x_i [\int_0^{\infty} Cr\{\xi_i \geq r\}dr - \int_{-\infty}^{0} Cr\{\xi_i \leq r\}dr]\right] \tag{16}$$

subject to

Equations (2)-(6).

Equation (13) lists risk minimization in the form of a variance. Equations (14) and (15) indicate risk minimization in the form of skewness and kurtosis criteria. Equation (16) maximizes the total E-project portfolio returns.

B. Defuzzification of the Proposed Model

To solve the proposed model, the presented model needs to be defuzzified first. To do this, the materials used in the previous section are used so fuzzy parameters are converted to crisp parameters.

According to Hao et al. [25], if a triangular fuzzy number is represented as (d_{1i}, d_{2i}, d_{3i}), the variance of this fuzzy number is calculated using (17):

$$\sigma_i = \frac{33 + 21\alpha_i^2\gamma_i + 11\alpha_i\gamma_i^2 - \gamma_i^3}{384\alpha_i} \quad (i = 1, \dots, n). \tag{17}$$

where α_i and γ_i are the maximum and minimum deviation of the fuzzy numbers that are calculated through (18)-(19):

$$\alpha_i = \max(d_{2i} - d_{1i}, d_{3i} - d_{2i}) \quad (i = 1, \dots, n), \tag{18}$$

$$\gamma_i = \min(d_{2i} - d_{1i}, d_{3i} - d_{2i}) \quad (i = 1, \dots, n). \tag{19}$$

Moreover, according to Hao et al. [25], the Skewness and Kurtosis of this fuzzy number are calculated through (20)-(21), respectively.

$$Sk_i = \frac{(d_{3i} - d_{1i})^2}{32}[(d_{3i} - d_{2i}) - (d_{2i} - d_{1i})] \quad (i = 1, \dots, n). \tag{20}$$

$$Ku_i = \frac{253\alpha_i^5 + 395\alpha_i^4\gamma_i + 17\alpha_i\gamma_i^4 + 290\alpha_i^3\gamma_i^2 + 70\alpha_i^3\gamma_i^3 - \gamma_i^5}{10.240\alpha_i} \quad (i = 1, \dots, n). \tag{21}$$

Finally, considering all the assumptions about optimizing the E-project portfolio, the proposed model that seeks to find an efficient boundary for investment with fuzzy information is presented as follows. In this model, fuzzy notations for all related parameters are shown.

$$\text{minimize} \left[\sum_{i=1}^{n} x_i \frac{33 + 21\alpha_i^2\gamma_i + 11\alpha_i\gamma_i^2 - \gamma_i^3}{384\alpha_i}\right] \tag{22}$$

maximize (23)

$$\sum_{i=1}^{n} x_i \left(\frac{(c_i - a_i)^2}{32} [(c_i - b_i) - (b_i - a_i)]\right)$$

minimize (24)

$$\sum_{i=1}^{n} \frac{253\alpha_i^5 + 395\alpha_i^4\gamma_i + 17\alpha_i\gamma_i^4 + 290\alpha_i^3\gamma_i^2 + 70\alpha_i^3\gamma_i^3 - \gamma_i^5}{10.240\alpha_i}$$

subject to

Equations (2)-(6) and Equations (18)-(19).

IV. Proposed NSGA-III-MOIWO

The proposed NSGA-III-MOIWO algorithm is developed by hybridizing NSGA-III and MOIWO algorithms. MOIWO algorithm is a numerical optimization algorithm inspired by weed growth in nature which was first introduced by Mehrabian and Lucas [26] for its single-objective version;

i.e., Invasive Weed Optimization (IWO). Some of the specific features of IWO compared to other evolutionary algorithms are the mechanisms of reproduction, spatial dispersal, and competitive exclusion [26]. Basically, weeds are very stable and adaptable to environmental changes. This algorithm works simply but efficiently in convergence to optimal solutions. As IWO has some strong operators to find neighborhood solutions, it has been selected to propose a hybrid algorithm in this research. By inspiring and simulating their properties and behavior, the authors developed a meta-heuristic optimization algorithm. It consists of the following steps:

A. Steps of the Proposed NSGA-III-MOIWO

To provide a new hybrid algorithm based on NSGA-III and MOIWO, the ideas presented in both algorithms are combined. The main idea of proposing such a hybrid algorithm is about the drawbacks of MOIWO. In the proposed hybrid algorithm, a crossover operator of the NSGA-III is employed for crossover and reproduction. The steps of the proposed NSGA-III-MOIWO algorithm are as follows:

Step 1. Generate a random population and evaluate their objective function.

Step 2. Reproduce based on the GA.

Sub-step 2.1. Use the roulette wheel method to choose two solutions randomly.

Sub-step 2.2. Apply the one-point crossover method to produce two new solutions.

Sub-step 2.3. Repeat Steps 1 and 2 to get the desired number of new solutions.

Step 3. Conduct competitive elimination based on the weed algorithm mechanism.

Step 4. Identify the non-dominated solutions and introduce them in Pareto fronts.

Step 5. Check the termination condition, if it is met go to Step 7, otherwise go to Step 6.

Step 6. Implement Niche preservation operator to specify the next generation solutions and go to Step 2.

Step 7. Report the best Pareto front. The pseudo-code of the proposed algorithm is presented in Fig. 2.

Proposed Hybrid meta-heuristic algorithm

```
1. Initialize first population S_i (i=1, …., N)
2. Evaluate the fitness of each solution F_i (i=1, …., N)
3. iter=1
4. repeat
5. for n=1: N step=2
6.    [Parent1, Parent2]=Rolllet_wheel (S)
7.    [Child(i), Child (i+1)]=Crossover (Parent1, Parent2)
8.  End for
9.  S=Competitive elimination (S, Child)
10. P= non-dominate solutions (S)
11. P*=Niche preservation (S, P)
12. iter = iter +1
13. Until iter >= Max_iterations
14. Output P*
```

FIGURE 2. **Pseudo-code of the proposed hybrid algorithm.**

B. Solution Representation, Encoding and Decoding Procedure

To display an E-project portfolio, an encoding procedure with floating values between 0 and 1 is used. The length of the solution representation is 2N, divided into two segments. The values in the first segment of the solution representation determine which E-projects are selected for the project portfolio. In the decoding procedure, elements with a value greater than 0.5, will be in the E-project portfolio. To determine the proportion of investment for each project, the second segment of the solution representation is used. Each number in this segment shows the percentage of investment. For example, Fig. 3 represents a solution for N=5.

Segment I: Project Selection					Segment II: Investment Proportion				
0.39	0.23	0.94	0.24	0.66	0.27	0.16	0.25	0.64	0.75
P1	P2	P3	P4	P5	P1	P2	P3	P4	P5

0	0	1	0	1	0%	0%	25%	0%	75%
P1	P2	P3	P4	P5	P1	P2	P3	P4	P5

FIGURE 3. **Solution representation for an example.**

In solution represented in Fig. 3, the projects of 3 and 5 have been selected and 25% of the capital is invested in project 3 and the rest is invested in project 5 which is a feasible solution.

In these circumstances, however, the budget constraints of the model may not be met. To convert the infeasible solution into the feasible one, a repairing mechanism is implemented.

V. Numerical Experiments

To verify the performance of the proposed NSGA-III-MOIWO, data on the returns of 125 active E-projects were collected from a construction company in Iran from 2015 to 2018. The raw data was the net profit of each 150 projects in each year from 2015 and 2018. By using these data, lower bound, middle bound and upper bound of the fuzzy return parameter is calculated. For each project, the lower bound is equal to the minimum profit between 2015 and 2018, the middle bound is equal to the average return in this period and the upper bound is the maximum profit from 2015 and 2015.

To evaluate the efficiency of the proposed hybrid algorithm, its performance is compared with two high-performance multi-objective evolutionary algorithms of NSGA-III and MOIWO [28-30]. The algorithms were coded in MATLAB® R2016 software and the results are reported and analyzed.

A. Input Parameters Settings

To implement and evaluate the proposed meta-heuristic algorithm, it was coded in MATLAB software. At each iteration, the value of the objective function, efficiency, and risk of the project portfolio, along with the runtime is reported. The parameters of the problem were set according to the list below:

Risk-averse coefficient: As outlined in Section III, in this algorithm, the risk factor is used to trace the efficient boundary, which is between 0 and 1. In this algorithm, in order to map the efficient boundary in each iteration, the risk-aversion coefficient varies by step size 0.1 unit. With this step size, 10 points of the efficient boundary will be achieved, which allows for an accurate comparison of the points.

Lower bound (ε_k) *and upper bound* (δ_k) *for each decision variable*: If there is a constraint associated with an investment in an E-project, the minimum and maximum ratio of investment in that project can be considered in the problem. In this research, for all selected E-projects, the minimum and maximum investment ratios are considered equal to 0.001 and 1, respectively.

Project portfolio size (K): This parameter specifies the number of E-projects to be selected for investment. In order to carefully examine the E-project portfolio optimization, the K value is 3, 5, 10, 20, and 50.

B. Implementation of the Algorithm

According to the descriptions, the algorithms of NSGA-III-MOIWO and NSGA-III were implemented on different project sizes and on different risk aversion coefficients, and finally, the related efficient boundaries for each E-project were plotted. Below are the results of each implementation:

When *K*=10

In the first step, the size of the E-project portfolio is equal to 10, and then for different values of the risk aversion coefficient, the returns and risk of investment as well as the value of the objective function are calculated.

The linear combination of risk and returns is calculated, and these results are shown in Table I.

TABLE I
RESULTS OF NSGA-III-MOIWO ALGORITHM WITH *K*=10

Risk-averse coefficient	Average return	Average risk	Weighted risk and return	Run time
0	1.60655	0.42381	-66.76246	1.13
0.1	1.62719	0.49068	-62.19488	1.63
0.2	1.54256	0.42846	-51.25705	1.20
0.3	1.78325	0.43758	-36.66555	0.98
0.4	1.58843	0.41655	-29.12275	1.07
0.5	1.41924	0.41642	-22.03702	0.82
0.6	1.57650	0.42500	-11.41377	1.08
0.7	1.42761	0.38871	-5.08311	0.90
0.8	1.47554	0.35763	2.29497	1.05
0.9	1.32827	0.95264	5.12966	0.96
1	1.60301	0.90195	8.87568	1.19
Average	1.54347	0.51267	-24.38512	1.09258

Table I indicates that with the increase of the risk averse coefficient (λ), the risk of the investment portfolio decreases. The reason for this behavior is that, by increasing the risk aversion coefficient, the effect of variance increases and the effect of the return decreases. This issue is solved with the NSGA-III algorithm. It should be noted that this algorithm does not need to convert risk and return to a goal due to its multi-objective general structure, and so both objectives can be optimized simultaneously. This process is also performed in the IWO algorithm. To better understand the performance of the three algorithms, it is necessary to examine the linear risk-return combination for different risk aversion coefficients. Fig. 4 represents the graph of the objective function resulted from each of the risk aversion coefficients.

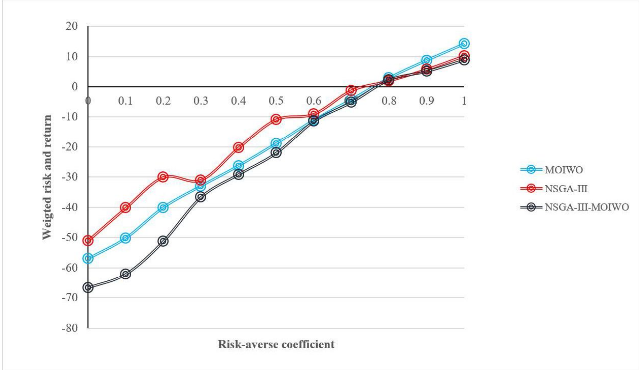

FIGURE 4. **Effective investment boundary for *K*=10.**

As can be seen, the values of the objective function for different risk aversion coefficients in Fig. 4 are well characterized by the difference between the solutions obtained from MOIWO and NSGA-III algorithm. Results show that the objective function of MOIWO was less than NSGA-III in terms of almost all different risk-averse coefficients except 0.8 and 0.9. Furthermore, NSGA-III-MOIWO algorithm has a significant superiority to the other two algorithms up to the risk aversion level. In other cases, it also has a good-enough advantage over other algorithms. Therefore, it can be concluded that this hybrid algorithm shows superior performance over the other two basic algorithms.

When *K*=50

The same procedure was performed for E-projects portfolio with a size of 50 E-projects, and the results are presented in Table II.

TABLE II
RESULTS OF NSGA-III-MOIWO ALGORITHM WITH *K*=50

Risk-averse coefficient	Average return	Average risk	Weighted risk and return	Run time
0	1.680	0.448	-35.507	0.929
0.1	2.949	0.004	-36.868	1.101
0.2	2.672	0.258	-32.530	1.132
0.3	2.103	0.158	-21.973	1.162
0.4	2.677	0.129	-20.132	1.311
0.5	1.596	0.142	-15.265	0.848
0.6	1.690	0.258	-6.201	0.961
0.7	1.958	0.664	-1.637	0.709
0.8	1.981	0.068	0.741	1.100
0.9	1.998	0.554	4.110	1.062
1	2.703	0.209	3.815	1.053
Average	2.182	0.263	-14.677	1.034

As shown in Table II, by increasing risk aversion, the return on investment portfolio decreases. The reason for this behavior is that when the risk aversion increases, the focus of the problem is to minimize the risk and pay attention to maximizing returns, leading to the lower objective function value. As illustrated in the previous process, in this example, the problem defined by the NSGA-III algorithm and the IWO algorithm is also solved and the values obtained are evaluated and schematically illustrated.

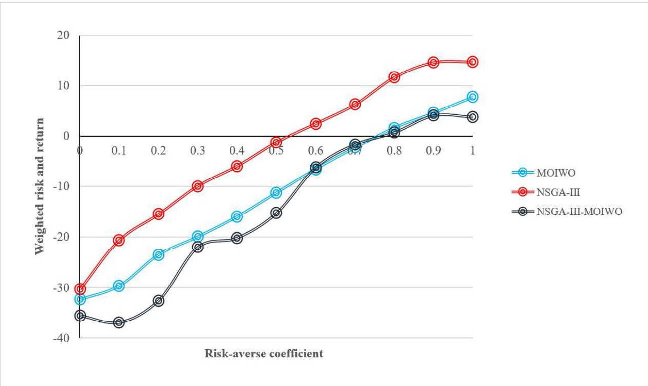

FIGURE 5. **Effective investment boundary for *K*=50.**

In Fig. 5, the value of the objective function is shown for a set of different risk aversion coefficients. As can be seen, in large dimensions for project sizes, the performance difference between MOIWO and the NSGA-III algorithm is very large, so that in all examples of MOIWO we have less objective function relative to NSGA-III algorithm. Also by increasing risk aversion, this difference gets even more than before. This shows that with the increase in the dimensions of the problem, the effectiveness of the MOIWO is more than other meta-heuristic methods. In examining the efficiency of NSGA-III-MOIWO algorithm, in all states, except for the 0.7 risk level, the output of NSGA-III-MOIWO is better than the other two algorithms. This superiority is reduced by increasing the risk aversion factor.

C. Evaluation of the Algorithms Convergence

One of the quality measures of meta-algorithms is how fast they convergence to desirable solutions. In this part of the numerical results, the convergence of the proposed hybrid algorithm is compared with the NSGA-III and MOIWO algorithms in terms of a different number of repetitions. In this regard, the replication number for each algorithm is considered to be equal to 100. The sum of the combination of risk combination and rational efficiency is calculated using the 50% risk aversion coefficient for each of these algorithms. The results for *K*=10 and *K*=50 are presented in Figs. 6 and 7.

The analysis of Fig. 6 shows that the NSGA-III-MOIWO algorithm has converged in iteration 50 while the NSGA-III algorithm has been replicated in iteration 60 and the MOIWO algorithm has been reached to iteration 65. On the other hand, the convergence number in the NSGA-III-MOIWO algorithm is lower than the other two algorithms. This suggests that the proposed algorithm of this study converges faster and provides a higher set of quality solutions.

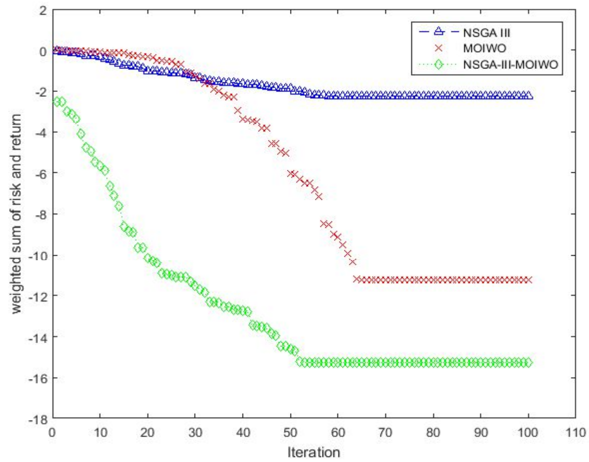

FIGURE 6. **Convergence analysis of the proposed algorithm for *K*=10.**

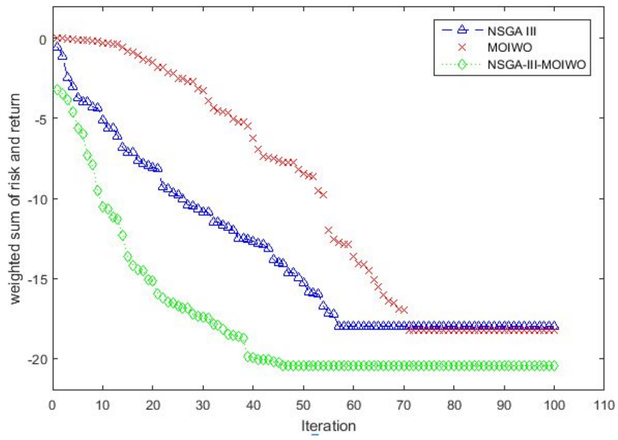

FIGURE 7. **Convergence analysis of the proposed algorithm for *K*=50.**

As shown in Fig. 7, the NSGA-III-MOIWO algorithm has converged to iteration 40. This situation happened for the NSGA-III and MOIWO algorithms in the iterations 58 and 71 respectively. Furthermore, the value that the NSGA-III-MOIWO algorithm is converged to it, is lower than the other algorithms. Taking the analysis of Figs. 6 and 7 into account, it indicates that with increasing the size of the E-project portfolio, the efficiency of the proposed algorithm will be higher in speed and quality than the other two algorithms.

D. Comparison with Well-Known Multi-objective Algorithms

Now, this subsection provides further investigation and validation on our proposed algorithm against well-known multi-objective meta-heuristic algorithms; i.e., NSGA-II, NSGA-III, MOIWO, Multi-Objective Particle Swarm Optimization (MOPSO) [31] using five measures. The obtained results are represented in Table III. Here, f^{best} and f^{worst} denote the best-found objective and the worst-found objective, respectively. The lower values for the Number of Fitness Evaluation (NFE) show the superiority of an algorithm. GAP index is calculated based on the best f^{best} that has been obtained by NSGA-III-MOIWO. As can be seen in Table III, NSGA-III-MOIWO outperforms the other algorithms.

As the reported results are in a multi-objective environment and some algorithms may find some suitable solutions in their Pareto optimal solutions, it is necessary to implement a comparison based on the statistical test between NSGA-III-MOIWO and other tested algorithms. Therefore, in order to have a comprehensive comparison between the studied multi-objective algorithms, the ANOVA test is applied in SPSS software under a 95% confidence level. The achieved results are summarized in Table IV.

In Table IV, *df* stands for the degree of freedom and Sig. is a significant level. As shown in Table IV, Sig. values are greater than the risk level (0.05) and it is concluded that all studded algorithms have a significant difference in Pareto optimal solution with each other. In order to find the best algorithm, the total sum of squares is checked. The sum of squares in NSGA-III-MOIWO is about 7356.3 which is lower than other algorithm and it can be concluded that the best Pareto solutions are obtained by NSGA-III-MOIWO algorithm.

TABLE III
COMPARISON RESULTS OF DIFFERENT ALGORITHMS

Portfolio size	Algorithm	f^{best}	f^{worst}-f^{best}	NFE	GAP (%)	Run time
	NSGA-III-MOIWO	-24.38	29.33	2179	0	1.09
	NSGA-III	-23.64	30.16	2896	3.12%	1.163
K=10	MOIWO	-21.27	30.47	2397	14.60%	1.131
	NSGA-II	-22.64	31.84	2164	7.70%	1.02
	MOPSO	-22.96	29.97	3410	6.17%	1.394
	NSGA-III-MOIWO	-14.67	37.94	2077	0	1.03
	NSGA-III	-15.33	44.16	2886	5.26%	1.109
K=50	MOIWO	-16.13	40.96	2647	2.13%	1.127
	NSGA-II	-16.48	42.75	1966	10.95%	0.967
	MOPSO	-15.09	43.96	3894	1.58%	1.678

TABLE IV
ANOVA TEST REPOT

Algorithms	Status	Sum of Squares	*df*	Mean Square	*F*	Sig.
	Between Groups	7329.144	10	732.9144		
NSGA-III-MOIWO	Within Groups	27.217	1	27.217	26.92855	0.1488
	Total	7356.361	11	-		
	Between Groups	7696.884	10	769.6884		
NSGA-III	Within Groups	25.388	1	25.388	30.31702	0.1404
	Total	7725.272	11	-		
	Between Groups	7671.997	10	767.1997		
NSGA-II	Within Groups	28.842	1	28.842	26.60009	0.1498
	Total	7700.839	11	-		
	Between Groups	7553.81	10	755.381		
MOIWO	Within Groups	28.088	1	28.088	26.89337	0.149
	Total	7581.898	11	-		
	Between Groups	7809.482	10	780.9482		
MOPSO	Within Groups	29.622	1	29.622	26.36379	0.1505
	Total	7839.104	11	-		

VI. Conclusion and Outlook

In this research, a new approach for E-projects portfolio on social media platforms were proposed and formulated by the use of a novel multi-objective meta-heuristic algorithm as NSGA-III-MOIWO. The proposed mathematical model aimed to minimize the risk of E-projects investment including variance, skewness and kurtosis while maximizing E-projects returns. To perform big-data driven decision-making, the cognitive computing system was taken into account to deal with the large amounts of data. The relationship between these two objectives was accomplished with a risk aversion coefficient. To solve this problem, a hybrid multi-objective algorithm based on NSGA-III and MOIWO (NSGA-III-MOIWO) was developed and implemented in MATLAB®. Then, the model was verified through solving different project portfolio problems and risk factors of various alternatives. Numerical results showed that the proposed hybrid algorithm has a higher performance than its two basic algorithms, namely NSGA-III algorithm and MOIWO algorithm. The proposed algorithm has the potential to solve the portfolio optimization problem in a limited amount of time, approximately 1 second. Moreover, an efficient comparison analysis including ANOVA statistical test was performed compared to NSGA-II, NSGA-III, MOIWO and MOPSO, and it was demonstrated that our proposed algorithm outperforms all the algorithms. Therefore, this algorithm can be considered as one of the most effective algorithms for optimizing E-projects portfolios.

For future research works, one can further investigate VaR and employ it as another well-known risk measure in the problem to have a more comprehensive evaluation regarding the risk of the E-projects portfolio. Moreover, the application of other uncertainty techniques in the problem can be an interesting research topic and the results can be compared with our proposed fuzzy model as well as with other approaches such as grey systems, robust optimization and stochastic programming.

REFERENCES

[1] M. B. Devereux and A. Sutherland, “A portfolio model of capital flows to emerging markets,” Journal of Development Economics, vol. 89, no. 2, pp. 181-193, 2009.

[2] H. Markowitz, “Portfolio selection,” The journal of finance, vol. 7, no. 1, pp. 77-91, 1952.

[3] Anavangot, V., Menon, V. G., & Nayyar, A. (2018, November). Distributed Big Data Analytics in the Internet of Signals. In 2018 International Conference on System Modeling & Advancement in Research Trends (SMART) (pp. 73-77). IEEE.

[4] Menon, V. G., & Khosravi, M. R. (2019). Preventing hijacked research papers in fake (rogue) journals through social media and databases. Library Hi Tech News.

[5] P. N. Kolm, R. Tütüncü, and F. J. Fabozzi, “60 Years of portfolio optimization: Practical challenges and current trends,” European Journal of Operational Research, vol. 234, no. 2, pp. 356-371, 2014.

[6] M. Ehrgott, K. Klamroth, and C. Schwehm, “An MCDM approach to portfolio optimization,” European Journal of Operational Research, vol. 155, pp. 752-770, 2004.

[7] K. J. Oh, T. Y. Kim, and S. Min, “Using genetic algorithm to support portfolio optimization for index fund management,” Expert Systems with Applications, vol. 28, no. 3, pp. 371-379, 2005.

[8] L. L. Macedo, P. Godinho, and M. J. Alves, “Mean-semivariance portfolio optimization with multiobjective evolutionary algorithms and technical analysis rules,” Expert Systems with Applications, vol. 79, pp. 33-43, 2017.

[9] K. Deb, A. Pratap, S. Agarwal, and T. A. M. T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182-197, 2002.

[10] E. Zitzler, M. Laumanns, and L. Thiele, “SPEA2: Improving the strength Pareto evolutionary algorithm,” TIK-report, 103, 2001.

[11] H. Babazadeh and A. Esfahanipour, “A novel multi period mean-VaR portfolio optimization model considering practical constraints and transaction cost,” Journal of Computational and Applied Mathematics, vol. 361, pp. 313-342, 2019.

[12] X.-T. Deng, Z.-F. Li, and S.-Y. Wang, “A minimax portfolio selection strategy with equilibrium,” European Journal of operational research, vol. 166, no. 1, pp. 278-292, 2005.

[13] X. Huang, “Two new models for portfolio selection with stochastic returns taking fuzzy information,” European Journal of Operational Research, vol. 180, no. 1, pp. 396-405, 2007.

[14] X. Huang, “Mean-semivariance models for fuzzy portfolio selection,” Journal of computational and applied mathematics, vol. 217, no. 1, pp. 1-8, 2008.

[15] M. Tavana, M. Keramatpour, F. J. Santos-Arteaga, and E. Ghorbaniane, “A fuzzy hybrid project portfolio selection method using data envelopment analysis, TOPSIS and integer programming,” Expert Systems with Applications, vol. 42, no. 22, pp. 8432-8444, 2015.

[16] F. Pérez, T. Gómez, R. Caballero, and V. Liern, “Project portfolio selection and planning with fuzzy constraints,” Technological Forecasting and Social Change, vol. 131, pp. 117-129, 2018.

[17] R. Saborido, A. B. Ruiz, J. D. Bermúdez, E. Vercher, and M. Luque, “Evolutionary multi-objective optimization algorithms for fuzzy portfolio selection,” Applied Soft Computing, vol. 39, pp. 48-63, 2016.

[18] K. Liagkouras and K. Metaxiotis, “Multi-period mean–variance fuzzy portfolio optimization model with transaction costs,” Engineering Applications of Artificial Intelligence, vol. 67, pp. 260-269, 2018.

[19] Y.-J. Liu, W.-G. Zhang, and W.-J. Xu, “Fuzzy multi-period portfolio selection optimization models using multiple criteria,” Automatica, vol. 48, no. 12, pp. 3042-3053, 2012.

[20] S.-T. Liu, “A fuzzy modeling for fuzzy portfolio optimization,” Expert Systems with Applications, vol. 38, no. 11, pp. 13803-13809, 2011.

[21] A. A. Najafi and S. Mushakhian, “Multi-stage stochastic mean–semivariance–CVaR portfolio optimization under transaction costs,” Applied Mathematics and Computation, vol. 256, pp. 445-458, 2015.

[22] P. Xidonas, C. Hassapis, J. Soulis, and A. Samitas, “Robust minimum variance portfolio optimization modelling under scenario uncertainty,” Economic Modelling, vol. 64, pp. 60-71, 2017.

[23] S. M. Seyedhosseini, M. J. Esfahani, and M. Ghaffari, “A novel hybrid algorithm based on a harmony search and artificial bee colonyy for solving a portfolio optimization problem using a mean-semi variance approach,” Journal of Central South University, vol. 23, no. 1, pp. 181-188, 2016.

[24] B. Liu, and Y. K. Liu, “Expected value of fuzzy variable and fuzzy expected value models,” IEEE Transactions on fuzzy systems, vol. 10, no. 4, 445-450, 2002.

[25] F.-F. Hao and Y.-K. Liu, “Mean-variance models for portfolio selection with fuzzy random returns,” Journal of Applied Mathematics and Computing, vol. 30, no. 1-2, p. 9, 2009.

[26] A. R. Mehrabian and C. Lucas, “A novel numerical optimization algorithm inspired from weed colonyization,” Ecological informatics, vol. 1, no. 4, pp. 355-366, 2006.

[27] K. Deb and H. Jain, “An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints,” IEEE

Transactions on Evolutionary Computation, vol. 18, no. 4, 577-601, 2013.
[28] A. Goli, E. B. Tirkolaee, B. Malmir, G.-B. Bian, and A. K. Sangaiah, “A multi-objective invasive weed optimization algorithm for robust aggregate production planning under uncertain seasonal demand,” Computing, vol. 101, no. 6, pp. 1-31, 2019.
[29] A. R. Pouya, M. Solimanpur, and M. J. Rezaee, “Solving multi-objective portfolio optimization problem using invasive weed optimization,” Swarm and Evolutionary Computation, vol. 28, 42-57, 2016.
[30] H. Li, K. Deb, Q. Zhang, P. N. Suganthan, and L. Chen, “Comparison between MOEA/D and NSGA-III on a set of novel many and multi-objective benchmark problems with challenging difficulties,” Swarm and Evolutionary Computation, vol. 46, 104-117, 2019.
[31] B. Wang, Y. Li, S. Wang, and J. Watada, “A multi-objective portfolio selection model with fuzzy Value-at-Risk ratio,” IEEE Transactions on Fuzzy Systems, vol. 26, no. 6, pp. 3673-3687.
[32] M. Mitchell, “An introduction to genetic algorithms,” MIT press, 1998.
[33] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by simulated annealing,” Science, vol. 220, no. 4598, pp. 671-680, 1983.
[34] F. Glover and M. Laguna, “Tabu search. In Handbook of combinatorial optimization,” Springer, Boston, MA, 2093-2229, 1998.
[35] S. Gupta, A. K. Kar, A. Baabdullah, and W. A. Al-Khowaiter, “Big data with cognitive computing: a review for the future,” International Journal of Information Management, vol. 42, pp. 78-89, 2018.

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